Neural Network based Short Term Forecasting Engine To Optimize Energy And Big Data Storage Resources Of Wireless Sensor Networks

Raja Vara Prasad Y, Rajalakshmi Pachamuthu
Department of Electrical Engineering
Indian Institute of Technology Hyderabad
Hyderabad, India
Email: [ee10p004 raji]@iith.ac.in

***Abstract*—Energy efficient wireless networks is the primary research goal for evolving billion device applications like IoT, smart grids and CPS. Monitoring of multiple physical events using sensors and data collection at central gateways is the general architecture followed by most commercial, residential and test bed implementations. Most of the events monitored at regular intervals are largely redundant/minor variations leading to large wastage of data storage resources in Big data servers and communication energy at relay and sensor nodes. In this paper a novel architecture of Neural Network (NN) based day ahead steady state forecasting engine is implemented at the gateway using historical database. Gateway generates an optimal transmit schedules based on NN outputs thereby reducing the redundant sensor data when there is minor variations in the respective predicted sensor estimates. It is observed that NN based load forecasting for power monitoring system predicts load with less than 3% Mean Absolute Percentage Error (MAPE). Gateway forward transmit schedules to all power sensing nodes day ahead to reduce sensor and relay nodes communication energy. Matlab based simulation for evaluating the benefits of proposed model for extending the wireless network life time is developed and confirmed with an emulation scenario of our testbed. Network life time is improved by 43% from the observed results using proposed model.**

***Keywords*-Clustered multi-hop network, Short term load forecasting, Power monitoring, Neural Network model, Big Data.**

I. Introduction

The IEEE 802.15.4 standard in [1] has become default protocol for low data rate and low power wireless sensor network (WSN) applications in industry, control, home automation, health care, and smart grids [2]- [3] finally evolving to Internet of Things (IoT). IoT has 50 billion devices connected by the year 2020 according to the report in [4]. Large number of devices with higher frequency data leading to Big Data, one would like to design more energy efficient wireless network thereby transforming in to **Green wireless networks**. Wireless networks without clock synchronization (asynchronous wireless network) can be opted for dense IoT networks to avoid complexity and central infrastructure.

More realistic case of correlated data has been considered in [5]- [12]. Energy efficient protocol with data fusion is proposed in [5]. Data centric routing advantage is investigated in [6] compared to traditional end-to-end routing. An estimate of the entire field within a prescribed distortion value by jointly compressing the data generated by different nodes is studied in [7]. Data aggregation without spatial correlation is well investigated in [8]. A greedy aggregation with path sharing is proposed in [9] to observe the energy savings and authors claim 45% of savings over opportunistic aggregation in high-density networks. Total transmission cost of transporting the information collected by the nodes to the sink node is minimized in [10] using a joint optimization of the rate allocation at the nodes and the transmission structure. Energy-latency trade-offs in wireless communication considering a data aggregation tree i.e a multiple-source single-sink communication paradigm is well studied in [11]. An improvement over LEACH protocol is achieved by proposing PEGASIS protocol in [12], where each node communicates only with a close neighbor and takes turns transmitting to the base station, thus reducing the amount of energy spent per round. Regardless of the techniques employed, existing studies miss data aggregation cost. The cost for data aggregation is negligible for some networks such as sensor networks monitoring field temperature may use simple average, max, or min functions. Complex networks which require hop-by-hop encryption and decryption at intermediate nodes will exponentially increase fusion cost.

Electrical load monitoring data with wireless sensor networks play an important role for electrical power operation. Accurate load forecast will lead to appropriate operation and planning for the power system, thus achieving a lower operating cost and higher reliability of electricity supply. Short-term load forecasting (STLF) plays a very important role in scheduling, economic dispatch and energy transactions with significant impact on the secure operation of power system [13]- [14]. Short-term load forecasting predicts electric loads for a period of minutes, hours, days or weeks. The short-term load forecasts has a significant impact on the efficiency of operation of any power utility [15]- [17]. Future loads can be extrapolated using the time series model assuming a stationary load series. Numerous forecasting methods are developed in the last years mentioned in [18]. These methods are mainly classified into two categories: classical approaches and artificial intelligence (AI) based techniques. Classical approaches are based on various statistical modeling methods using a mathematical combination of previous load values and even other variable such as weather data to predict future load values. Classical STLF approaches utilizes the concept of regression exponential smoothing, autoregressive integrated moving average (ARIMA), Box-Jenkins and Kalman filters. Recently several research groups have studied the use of artificial neural networks (ANNs) models and Fuzzy neural networks (FNNs) models for load forecasting [19]. Researchers are able to forecast using FNN and ANN with the back propagation method effectively in past few years.

Major contribution of this paper is to develop an energy efficient transmit policies for dense wireless sensor network using a historical data base thereby increasing network life time. Integrated Artificial Neural Network (ANN) model with day ahead decision algorithms is proposed to forecast sensor data day ahead and optimally schedule sensor nodes for next day. User defined tolerance policies and decisions are part of the algorithms integrated to the ANN model to generate transmit schedule vectors for each and every sensor.

Rest of this paper is organized as follows. Section-II explains the proposed integrated NN model. Neural Network (NN) model and Short term forecasting is given in Section-III. Results of NN model and energy benefits of the proposed system for an example emulation scenario is discussed in Section-IV. Finally Section-V concludes with future scope of the work.

II. System Model

Proposed system is a wireless Cyber Physical System (CPS) with a centralized sink/gateway with distributed sensors and relay nodes as shown in the Fig. 2. Sensor data is forwarded to gateway through relay node multi-hop communication. Relay nodes forward data to nearest next hop by randomly selecting a relay node by broadcasting beacons which is known as any cast routing. Any cast routing in the proposed model is the generic routing that can scale multi-hop networks to very large networks enabling IoT applications. Though model proposed can be adapted to wired/wireless medium, all nodes i,e sensor, relay and gateway are wireless sensor nodes in this paper. Functional architecture of the proposed system is shown in the Fig. 1. Each sensor data collected at the gateway is maintained as database. Historical data of each sensor is given as inputs to NN algorithm to produce day ahead prediction of sensor values. These predicted values along with application constraints are used to generate day ahead transmit vectors of sensors at the gateway shown in the Fig. 1. Application requirements like Percentage of variation that can be considered negligible/redundant from the present data to immediate previous data can be database collected from experts. Sensor data of the present day is sent to gateway according to day ahead transmit schedule vector to store in database for application requirements. Assumptions made in developing the proposed model are given as follows:

- All wireless nodes are assumed static

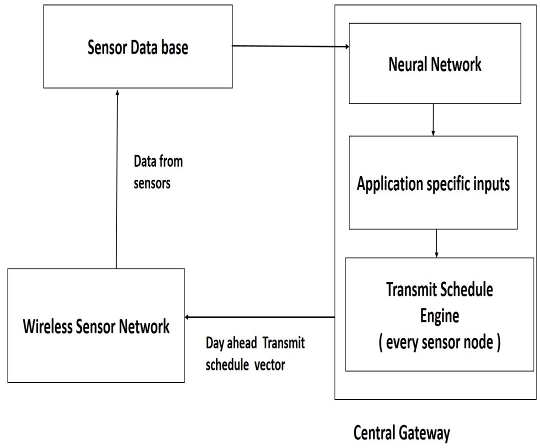


Fig. 1: Block diagram of the proposed system architecture

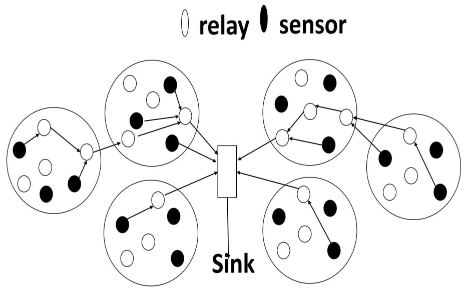


Fig. 2: System Model of the proposed System

- Gateway has higher level of computational and power resources.
- Gateway is connected to mains supply and transmit energy optimization is not considered for the gateway.
- All relay nodes forward data by randomly selecting a nearest relay node known as anycast routing in the literature.
- Sensor nodes only samples and transmits data to relay node but do not participate in the routing.
- Historical database of every sensor is maintained to update the Neural network regularly.

III. Neural Network model

Proposed model in this paper is developed to optimize transmit schedules of a sensor node by predicting data with Neural network short term forecasting engine. Eventhough proposed model in this paper can be generalized for any server with a historical database, but it targeted for building power monitoring application in this paper using a multi-hop wireless sensor network. Development of proposed model is initiated with developing a Neural network (NN). NN model in this paper utilizes nntool box to develop a short term load forecasting model to finally arrive at optimal transmit energy algorithm of a wireless sensor network. Popular training algorithms to mention are Back propagation (BP), Deep Learning and Levenberg-Marquardt. BP algorithm has a slow

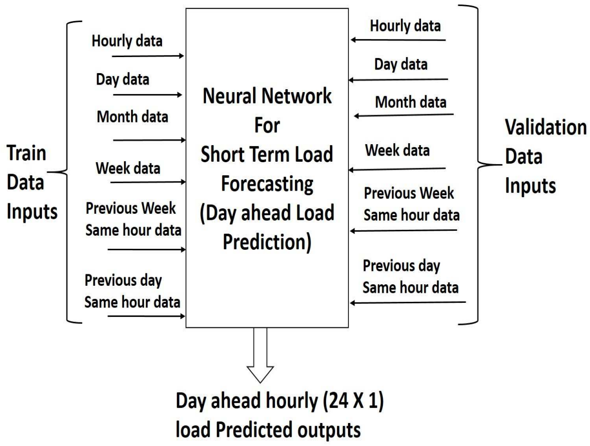


Fig. 3: Neural Network of Short term load forecasting (Day ahead)

learning convergent velocity and may be trapped in local minima, where Deep learning algorithms suffer with over fitting and higher computational time problems. Levenberg-Marquardt (L-M) combines the best features of the Gauss-Newton technique and the steepest-descent method, which allows to converge faster than conjugate gradient methods since the Hessian Matrix is not computed but only approximated. L-M algorithm uses the Jacobian that requires less computation than the Hessian matrix. Training algorithm used in the model is Levenberg-Marquardt. NN model was run with training data with multiple epochs, where each epoch was running for number of iterations. Weights are adjusted by checking Mean Absolute Error (MAE). NN model is initialized with 4 neurons first and gradually increased till the network fit with a desired accuracy of 5% MAE and number of neurons are 20 at this accuracy. Validation data is also fed into the model as shown in the Fig. 3. Finer details of the model are given below along with application specific details.

A. *Neural Network based Short term load forecasting*

Neural network model considered for the short term load forecasting simulation is shown in the Fig. 3. Short term load forecasting of a load can be effectively realized with different abstractions of historical database. These fields include *Hourly, Day data, Month data, Week data, Previous Week Same hour data and Previous day Same hour data* shown in the Fig. 3. Neural Network is created to form a load behavioural network using the above inputs. Data is divided into training (60%), validation (30%) and test data (10%). NN model is tested and validated with data base and results obtained are used in generating optimal transmit schedules of wireless sensor network. Energy savings of the proposed model is also investigated with Matlab simulations in the later subsections of this paper. Detailed description of Neural network and decision engine is explained in the following subsection. Developed NN model is tested with 2 databases. Data base of one year from power plant of Perak state in Malaysia [21] and the

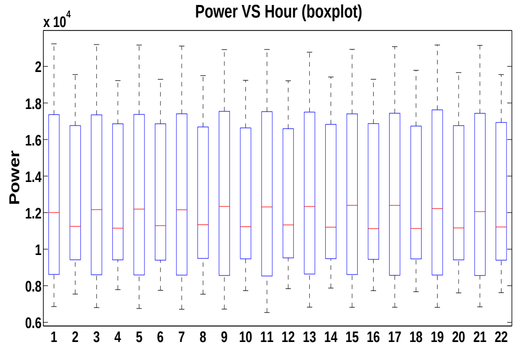


Fig. 5: Box plot of hourly power pattern for one month at IIT Hyderabad test bed

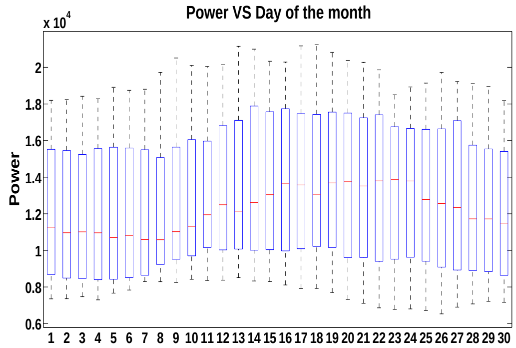


Fig. 6: Power pattern for 30 days at IIT Hyderabad test bed

second database is One month load data collected at IIT Hyderabad test bed. Results and observations of both data sets are explained in detail in the following sections.

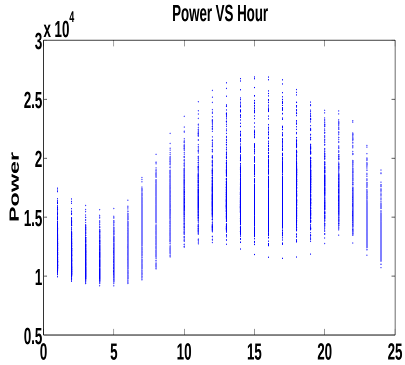
IV. Results observed from Proposed model

Results obtained from the validation of proposed model are divided into 3 subsections as given below.

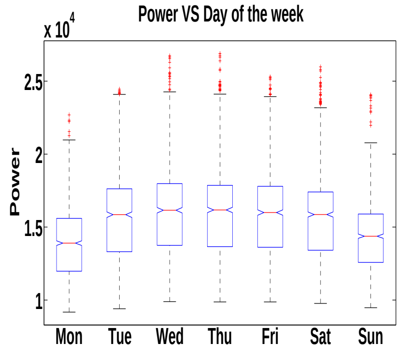
- Results observed from NN model using database-1.
- Results observed from IIT Hyderabad test bed.
- Energy saving's of the proposed model.

A. *Results observed from Neural Network using database-1*

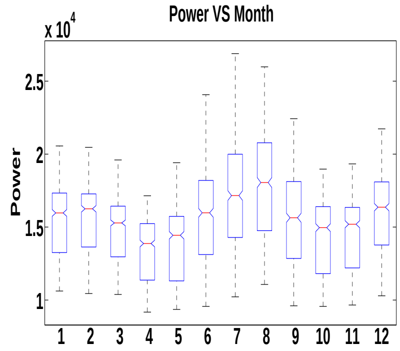
we started our NN model validation with open database of Perak state power plant in Malaysia [21] which has total of one year hourly data starting from July 2005 to June 2006. Data from power plant is used as historical data base to the Neural network to generate day ahead predictions of each sensing module. Historical online data base [21] of one year power monitoring data averaged for every one hour as shown in the Fig. 4(a). Data is segregated into hourly, daily, weekly, monthly, previous day and week data shown in Fig. 4(a), 4(b) and 4(c). Power consumption pattern observed from database is not uniform through out the week, month and year from Fig. 4(a), Fig. 4(b) and Fig. 4(c). From Fig. 4(b), power consumption has peak demand during Wednesday and Thursday and minimum on Monday. Segregated data from



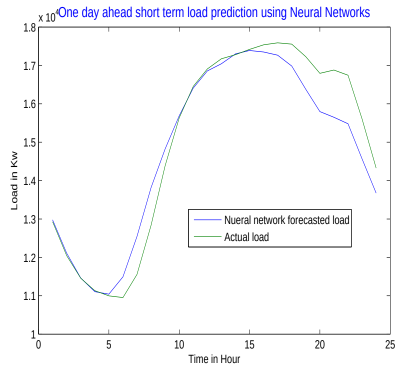
(a) Power vs hour



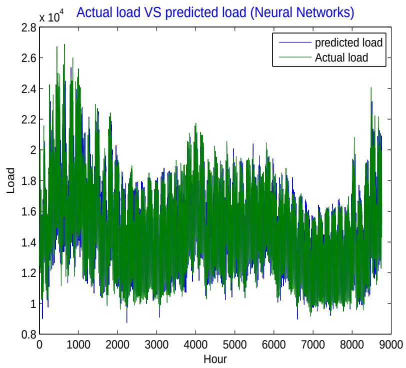
(b) Power pattern for a week



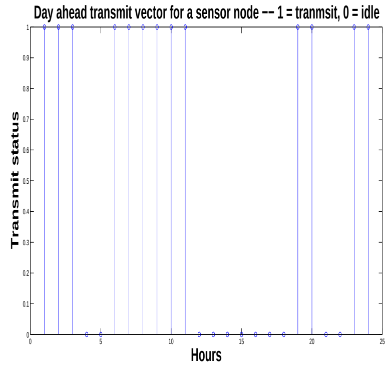
(c) Power pattern for 12 months



(d) Forecasted Vs actual load for one day



(e) Forecasted Vs actual load for one year



(f) Day ahead transmit vector for a sensor node

Fig. 4: Historical database of Perak state power plant segregated into different input vectors of NN model and Output generated from the model. Power pattern for a) Hour b) Week c)Year and d) Comparison of forecasted Vs actual power for one day e) Comparison of forecasted Vs actual power for one year f) Example day ahead transmit vector

database is taken as inputs to the NN model shown in the Fig. 3. NN model is trained with input streams and captured the behaviour of load thereby predicting the behaviour of load for next 24 hours. Predicted load using above NN for next 24 hours (1-July-2006) using 1 year data i.e from June 2005 to June 2006 is shown in the Fig. 4(d). Neural Network predicted load matches with monitored load of 1-July-2006 with less than 4.5 % mean absolute percentage error. Results show that our NN predictor results are accurate enough to predict steady state behaviour of sensor data for a short term duration of one day. Above results are used in generating transmit vector and thereby computing energy savings of the proposed model explained in the next subsection named as Energy savings of the proposed model.

B. Results observed from IIT Hyderabad test bed

Power monitoring of our Institute building at IIT Hyderabad is the recent initiative under CPS project to transform existing buildings into Green buildings. Power monitoring using Wi-Fi module is designed to monitor any electrical load of the home/building shown in the Fig.7. Power consumption of different loads situated in the labs of IIT Hyderabad is monitored at periodic intervals from September 2014. Power sensing nodes shown in Fig. 2 are either IEEE 802.15.4 [22] or IEEE 802.11 wireless devices [23] which serves as back bone to forward data from all individual sensor nodes to central sink through single-hop or multi-hop communication. Power is monitored at regular intervals of one minute using a sensing module developed at IIT Hyderabad. Data sent to gateway is maintained in database averaging for every one hour. Power monitoring data of one month averaged for every one hour at IIT Hyderabad is shown in the Fig. 5 and Fig. 6. Fig. 5 plots Power Vs Time in hours. Time scale is plotted for 22 hours as other two hours is scheduled power cut in this area, which is not considered. Power consumption pattern of September month of 2014 is shown in Fig. 6. One month database is also used to predict day ahead load forecasting. It is observed from the results of NN model that mean absolute percentage error is around 30% which is very high. Large error with our database is due to insufficient data, (only one month data 30 x 24 vector compared to first database of 365 x 24) due to which the NN model failed to converge. It is observed from the results that after collecting sufficient data our testbed data can be used to form accurate NN model in the future such that day ahead transmit vectors can be generated for wireless sensor network at IIT Hyderabad. A simulation model of wireless network along with above NN model is realized in Matlab to observe

Tx_v[1-6]	1	1	1	0	0	1
Tx_v[7-12]	1	1	1	1	1	0
Tx_v[13-18]	0	0	0	0	0	0
Tx_v[19-24]	0	0	0	0	1	1

TABLE II: Transmit vector (Tx_v) generated for the example forecast day ahead vector L_f in Table. I

the transmission energy savings of sensor nodes. Details of this simulation are followed in the next subsection.

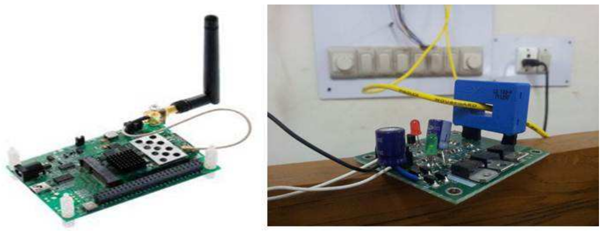


Fig. 7: Power monitoring module with IEEE 802.11 (Wi-Fi) communication device

C. *Energy savings observed from the proposed model:*

Communication energy of the wireless network can be optimized by minimizing redundant data transmission from sensor to the sink. Transmit energy is calculated for every sensor node in the wireless network deployed at IIT Hyderabad based on the proposed model. Transmit schedule vector for each sensor node is generated at the sink. These vectors are generated using a simple decision engine based on percentage variation of the present sample compared to immediate previous sample generated from the NN model day ahead forecasted data. Example tolerance calculation is shown in the Eq. 1, where S_i and S_{i+1} are consecutive samples of a forecasted day ahead load data of a sensor. If Tolerance T_{i+1} from Eq. 1 is less than defined tolerance *T*, then there is no need to transmit present data which is indicated as zero in transmit vector Tx_v of sensor node. Transmit vector (Tx_v) of a sensor node is represented by 6X4 matrix where each element is either a binary decision of transmit or no transmit in Table. II and 24 samples of forecast day ahead vector L_f in Kilowatts is shown in Table. I. Sink node maintains a Tx_v vector for each sensor node and does not expect a packet when there is a zero in the present hour slot and consider previous sample value in the present hour slot shown in the Fig. 8. Fig. 8 plots comparison of load data from proposed model and actual load monitored at every hour. Mean Absolute Percentage Error (MAPE) of forecasted Load from actual load over total online database is calculated and found that MAPE is less than 1.5%.

$$T_{i+1} = (S_{i+1} - S_i)/(S_i) \tag{1}$$

Transmit vectors are generated and transmit energy is calculated considering the standard values of hardware platform TelosB from the datasheet in [20]. An example calculation

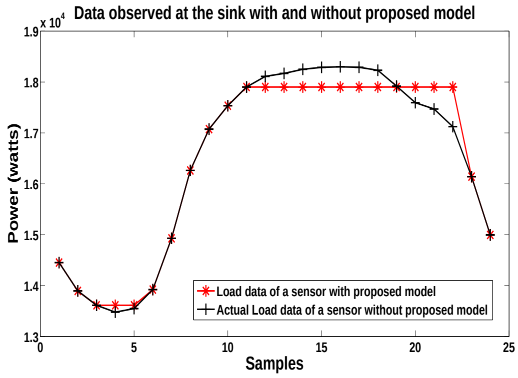


Fig. 8: Comparison of Load observed from proposed model and Actual load

for the IEEE 802.15.4 based wireless network deployed at IIT Hyderabad shown in Fig. 2 is given in detail as below. Number of sensor and relay nodes in network from the Fig. 2 is 18 and 21 respectively. Every sensor node will forward power data to sink through single hop or multi-hop communication depending on distance to the sink. Most of the sensors are two hops away from the sink and very few sensors need more than 2 hops to reach the sink as shown in the Fig. 2. For example sensor node S_1, S_2, S_3 and S_4 are 1,2,3 and 4 hops respectively away from the sink. If a sensor node S_4 wants to transmit a hourly periodic packet to sink, there should be at least 4 transmissions to reach sink. If the current sample of sensor node S_4 is just a redundant or same sample as previous, then transmitting present packet will result in unnecessary wastage of 4 transmissions at 4 nodes. Transmission energy will get multiplied by number of hops depending on the distance the sensor is located from the sink. NN based short term forecasting will assist nodes in their optimal transmit strategy. Though proposed model is simulated for an example network in Fig. 2, with any cast routing wireless networks can easily scale to large area making them suitable for IoT applications. In any cast routing relay nodes share the network load equally on an average due to which energy saving of a relay node in a particular route is sufficient to account total energy savings of the network. Though this method is very much applicable to all types of sensors when there is sufficient historical data at the sink, we implemented on power monitoring of electrical loads in our IIT Hyderabad institute building. Matlab code is written to compute this transmit energy for the network shown in Fig. 2.

Matlab based emulation code is developed to compute transmit energy savings of the proposed model. After running a NN model with historical data, a 24 x 1 day ahead transmit vector is generated for each sensor node. Anycast routing is assumed for all sensor and relay nodes in establishing a multi-hop communication. Route table is generated using a random selection of available neighbor relay nodes to account for the number of hops involved in order to transfer each data packet from respective sensor node. Total transmit energy of

L_f[1-6]	14.454	13.896	13.614	13.479	13.550	13.924
L_f[7-12]	14.930	16.263	17.074	17.535	17.902	18.111
L_f[13-18]	18.169	18.250	18.288	18.300	18.289	18.231
L_f[19-24]	17.919	17.594	17.470	17.123	16.141	14.996

TABLE I: Example forecast day ahead vector L_f in Kilowatts

a link increases by *n* folds with *n* number of hops. Transmit energy with out proposed model is also computed for the same anycast routing and periodic redundant data. All energy results are averaged over 50 iterations and it is observed that there is at least 43.04$\%$ savings in the total network energy with proposed model which is significant amount of reductions. It is observed from results that simple data prediction and analysis can reduce large wastage in communication energy. Proposed model can benefit the large network applications like IoT by reducing redundant data into Big Data servers, such that a lot of energy and storage aspects can be improved for future applications. Proposed model also extends network life time of a battery powered wireless ad hoc networks.

V. Conclusion

Wireless sensor network redundant data transmission is minimized by proposing a steady state short term day ahead forecast model of each sensor. Model proposed is generalized to multi-hop networks using anycast routing. Matlab based Neural Network model is developed and tested with one year open historical power database and one month IIT Hyderabad test bed data to generate one day ahead prediction of power data. Results show that NN model developed can capture the behaviour of load with less than 4.5$\%$ mean absolute error using one year historical power database. Transmit vectors schedules of sensors are generated and transmit energy savings is computed with Matlab emulation of IITH wireless network and NN simulation models. Reduction in transmit energy is also observed to be atleast 43$\%$ for considered short term load forecasting application. Adaptive rule engine and generalized NN model for all types of sensors application to reduce redundant data there by making Big data servers more efficient is the future scope of research.

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